Performance Analysis of Features for Personnel Recognition Using Multistatic Micro-Doppler

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***Abstract*—In this letter we investigate the use of micro-Doppler signatures experimentally recorded by a multistatic radar system to perform recognition of people walking. Three different sets of features are tested, taking into account the impact on the overall classification performance of parameters such as aspect angle, types of classifier, different values of Signal-to-Noise-Ratio, and different ways of exploiting multistatic information. High classification accuracy of above 98% is reported for the most favorable aspect angle, and the benefit of using multistatic data at less favorable angles is discussed.**

***Index Terms*—Multistatic radar, micro-Doppler, feature extraction, target classification**

I. Introduction

Additional modulations on top of the main Doppler shift generated by a moving person are known as micro-Doppler signatures and are related to the motions of limbs and body [1]. A good review of different applications and uses of human micro-Doppler signatures can be found in [2]. Some include the discrimination between different activities such as walking, running, crawling [3], the possibility of distinguishing human from animals such as dogs or horses, and vehicles [4], and the characterization of free and confined movement of arms related to carrying objects, potentially weapons in some context [5-6]. In all these applications numerical features are extracted from the micro-Doppler signatures and used as input to classifiers. One of the well-known problems in micro-Doppler based classification is the effect on the overall micro-Doppler signature of the aspect angle between the velocity vector of the moving body parts and the line-of-sight of the radar. If this angle has limited values up to approximately 30°, the classification performance appears not to present excessive degradation [2], but for higher angles up to the case limit of 90° the classification is severely hindered [7]. Bistatic and multistatic radar has been suggested as a possible mitigation to this problem [8-10], as the deployment of multiple nodes can provide multi-perspective views on targets, where at least one node can illuminate the target at a favorable aspect angle.

Little work is available in the literature on the use of micro-Doppler signatures to identify and recognize different people performing the same activity. This task is expected to be more challenging and therefore require more robust features than classifying between different activities, as the possible targets, i.e. different human subjects, will not be too dissimilar from one another and generate similar signatures. In [11] the authors proposed features based on Cadence Velocity Diagram to discriminate between four subjects running and walking with data extracted from a CW X-band radar. The subjects were moving on a treadmill in indoor controlled tests and classification accuracy above 90% was reported with these data. In our work in [12] we showed preliminary results of using a feature extracted from Singular Value Decomposition (SVD) to identify different people walking on a trajectory perpendicular to the baseline. The feature is extracted from the whole matrices derived from SVD rather than from individual singular vectors.

In this letter the classification performance of this novel SVD-based feature and of features based on the centroid of the micro-Doppler signatures is investigated and compared as a function of different operational parameters using experimental multistatic data. Three different aspect angles and considered and six types of classifiers with different complexity used to perform classification. The robustness of these features as a function of the Signal-to-Noise-Ratio (SNR) is also investigated, as well as the computational efficiency of the different classifiers and features combinations.

The rest of the letter is organized as follows. Section II presents the radar system and the experimental setup. Section III describes the different features and the investigation of their classification performance. Section IV concludes the paper.

II. Radar System and Experimental Setup

The data processed in this letter were collected using the multistatic radar system NetRAD, developed at University College London in the past few years and used for previous human micro-Doppler measurements [6, 9]. NetRAD is a coherent pulsed radar with three separate but identical nodes operating at 2.4 GHz (S-band). The RF parameter used for the data collection were linear up-chirp modulation with 0.6 µs duration and 45 MHz bandwidth, 5 kHz pulse repetition frequency (PRF) to ensure that the whole human micro-Doppler signature was contained in the unambiguous Doppler region, and 5 s duration of each dataset to record multiple periods of the average human walking gait. The transmitted

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power was approximately 200 mW. Vertically polarized antennas with 24 dBi gain and approximately 10°×10° degrees beamwidth were used.

The experiment took place in an open field at the UCL Sports Ground in December 2014, and the experimental setup is shown in Fig. 1. The three nodes were deployed along a linear baseline with 40 m inter-node separation and the target was located at 70 m from the baseline. Node 3 was used as monostatic transceiver, whereas Node 1 and 2 as bistatic receiver-only nodes. The resulting bistatic angles were therefore 30° and 60° for Node 1 and 2, respectively. As in Fig. 1, separate recordings with the target walking towards one of the node were collected, generating data with three different aspect angles with respect to the line-of-sight of the transceiver node, namely 0° (angle 1), 30° (angle 2), and 60° (angle 3). Three different subjects took part in the experiment. The key body parameters were 1.70 m, 69 kg, average body type for subject 1, 1.77 m, 65 kg, slim body type for subject 2, and 1.87 m, 90 kg, average body type for subject 3. All the subjects were male. The total number of recordings was therefore 135, assuming 3 subjects, 3 nodes, 5 repetitions of the movement, and 3 aspect angles.

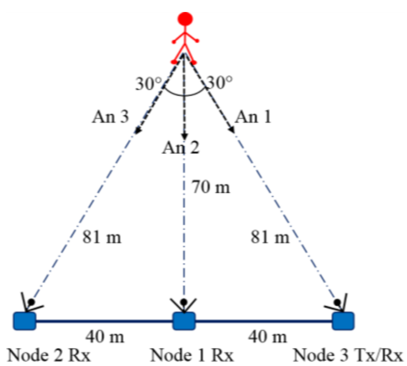

Fig. 1. Experimental setup with radar nodes and target

III. Data Analysis

The micro-Doppler signatures were extracted from the data using a Short Time Fourier Transform (STFT) calculated with 0.3 s Hamming window and 95% overlap. An example of monostatic micro-Doppler signatures for the three subjects walking towards the transmitter node are shown in Fig. 2. Differences between the signatures of different subjects can be seen, particularly in the positive/negative peaks due to the movement of the limbs and in the shape and consistency of the main component due to body swaying.

Numerical features to quantify these differences and use them in automatic classifiers are explored in the rest of this section. Prior to feature extraction, each spectrogram was divided into 1 s long blocks to generate 675 blocks, i.e. five times the total number of recorded datasets.

Many parameters can have an impact on the overall classification performance of a multistatic radar system [13]. The analysis in the rest of this section focuses on some of them, namely the different features (either based on SVD or on the centroid of the micro-Doppler feature), the aspect angle, the classifier types, the different approaches in combining multistatic information, and the SNR. Other parameters are kept constant during this analysis, namely the operating frequency of the radar (S-band, 2.4 GHz), the PRF (5 kHz), the dwell time to extract feature samples (1 second), the size of the samples database and the percentage used to train the classifier (675 samples per feature, 20% training).

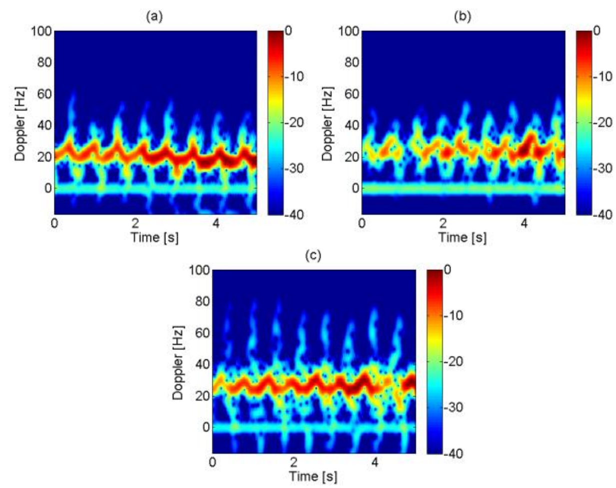

Fig. 2. Spectrograms of micro-Doppler signatures extracted from monostatic data for subject 1 (a), subject 2 (b), and subject 3 (c), all at aspect angle 1

A. Feature extraction and classification

SVD was applied to the micro-Doppler signatures to extract the first two considered features. Given the matrix M of the micro-Doppler signature, the SVD decomposition is simply given by $\mathbf{M} = \mathbf{USV^T}$, where **U** and **V** are the matrices containing the left and right singular vectors respectively, and **S** is the diagonal matrix with the singular values of **M**. The first feature is given by the standard deviation of the first right singular vectors from **V**. This feature was used to successfully classify unarmed vs armed personnel in [14]. Features extracted from few singualr vectors have been also reported for the classification of different types of micro-drones [15].

The second feature considers the whole matrices **U** and **V** rather than individual singular vectors. It has been shown that the sum of the intensity of the elements of **U** can be an effective feature for personnel recognition [12].

The third set of features is extracted from the centroid and the Doppler bandwidth of the micro-Doppler signatures as in (1) and (2), respectively, where f_C is the Doppler centroid, B_C the bandwidth, and $S(i,j)$ the spectrograms at the i^{th} Doppler bin and j^{th} time bin. The centroid is an estimate of the centre of gravity of the signature, and the bandwidth estimates the intensity of the signature around it. The mean and the standard deviation of centroid and bandwidth are used as features. These four features are used together as input to the classifiers.

$$f_c(j) = \frac{\sum_i f(i) S(i,j)}{\sum_i S(i,j)} \quad (1)$$

$$B_c(j) = \sqrt{\frac{\sum_i (f(i) - f_c(j))^2 S(i,j)}{\sum_i S(i,j)}} \quad (2)$$

The different types of classifiers used in this letter are diagonal-linear discriminant analysis (DLDA), diagonal-quadratic discriminant analysis (DQDA), naïve Bayes with kernel functions estimators (NB), nearest neighbors with 3 samples (NN3) and 5 samples (NN5), and classification tree (CT). These are described in more detail in [16]. These classifiers were trained with 20% of the available feature samples, and the remaining samples used to test the performance and determine the error as total number of misclassification events over the total number of samples. The consistency of the performance was evaluated with 100 tests for each classifier using random sample selections for training. The average classification error over these 100 repetitions was calculated and in here the percentage accuracy is reported as 100% minus such error.

The classification accuracy using the three aforementioned features is reported in tables 1, 2, and 3, respectively. Three different approaches to use multistatic data are compared with the conventional use of only monostatic data. In the first approach feature samples from all radar nodes are used at a single classifier generating the final decision. In the second approach separate classifiers use feature samples of each radar node generating partial decisions, which are then combined through a binary voting procedure, i.e. the final decision has to be voted by two of the three nodes. The last approach considers the level of confidence of each partial decision with a threshold. When two nodes agree on a partial decision with confidence higher than the threshold, they generate the final decision. But if one of the two has lower confidence, and at the same time the third node has higher confidence than the other two nodes, then the final decision is generated by the third node. This approach aims at preventing that two nodes with low confidence may lead to a misclassification event. The threshold was set at 65%, the value providing the best classification after tests with values between 55% and 75% with the available data. In both second and third approaches, the final decision is generated by the node with highest confidence if there is no partial decision reached by at least two nodes.

Table 1, 2, and 3 presents the classification results for the three aforementioned features. The first feature related to an individual singular vector appears to be not suitable for this task of personnel recognition, as the accuracy is below 70%. On the contrary, both the features based on whole SVD matrix and centroid provide good classification results, with accuracy above 98-99% for the former when the voting with threshold approach is used to combine multistatic data. Chosen the type of features, the performance appears to be quite regular for different types of classifiers. It is shown that with the proposed features the separate classification approach yields better results than using a centralized classifier for all multistatic data. This was already observed in previous works [9, 12, 14].

B. *Effect of aspect angle and SNR*

Table 4 presents the classification results for the different aspect angles and classifiers considered in this letter when multistatic data are combined with the voting with threshold approach. Only centroid features and features based on the whole SVD matrix are considered. Given the aspect angle, the classification accuracy appears to be quite consistent with different classifiers. SVD features provide better accuracy than centroid features, and this appears to be consistent for each aspect angle. The best classification results are obtained for aspect angle 2 (accuracy above 97% for SVD features), whereas the classification performance degrades significantly at aspect angle 3 for both types of features. This performance reduction is expected, as aspect angle 3 is equal to 60° with respect with the monostatic line-of-sight, hence the least favourable angle among those considered.

TABLE I
CLASSIFICATION ACCURACY FOR DIFFERENT CLASSIFIERS AND METHODS OF COMBINING MULTISTATIC DATA – FEATURE EXTRACTED FROM SVD VECTOR

Classifier Type	Mono data only	All multi data	Binary voting	Threshold voting
DLDA	62.6	54.6	64.3	66
DQDA	62.2	54.7	63.3	65
NB	64.6	55.1	63.9	64.7
NN3	65.1	52.1	62.8	65.7
NN5	64	53	62.5	64.7
CT	68.5	53.6	67.1	67

TABLE II
CLASSIFICATION ACCURACY FOR DIFFERENT CLASSIFIERS AND METHODS OF COMBINING MULTISTATIC DATA – FEATURE EXTRACTED FROM SVD MATRIX

Classifier Type	Mono data only	All multi data	Binary voting	Threshold voting
DLDA	98.9	72.2	98.8	99.4
DQDA	97.6	72.2	98.9	98.9
NB	95.4	72.1	97.9	97.5
NN3	98.7	71.1	99.4	99.4
NN5	98.7	70.9	99.1	99.4
CT	98.8	71.3	99.6	99.6

TABLE III
CLASSIFICATION ACCURACY FOR DIFFERENT CLASSIFIERS AND METHODS OF COMBINING MULTISTATIC DATA – FEATURE EXTRACTED FROM CENTROID

Classifier Type	Mono data only	All multi data	Binary voting	Threshold voting
DLDA	91.6	76.7	91.1	92.2
DQDA	88.6	75.8	89.7	90.3
NB	84.1	75.3	84.9	85.3
NN3	89.8	76.9	87.8	88
NN5	89	75.6	86.2	88.3
CT	85.5	77.7	86.7	86.7

TABLE IV
CLASSIFICATION ACCURACY FOR DIFFERENT CLASSIFIERS AND ASPECT ANGLES – MULTISTATIC DATA COMBINED WITH THRESHOLD VOTING

Classifier Type	SVD matrix feature			Centroid features		
	An 1	An2	An 3	An 1	An2	An 3
DLDA	92.7	99.4	76.2	93.5	92.2	77.2
DQDA	92.8	98.9	75.5	91.8	90.3	75.3
NB	91.2	97.5	75.0	87.7	85.3	70.5
NN3	93.3	99.4	76.3	91.2	88.0	69.3
NN5	92.5	99.4	75.6	88.0	88.3	66.1
CT	93.4	99.6	76.9	87.9	86.7	70.1
AVERAGE	92.7	99.0	75.9	90.0	88.5	71.4

The effect of the SNR is investigated in tables 5 and 6 for different classifiers, respectively for centroid features and SVD features. Only results related to aspect angle 2 are reported in these tables. The voting with threshold approach was used to combine multistatic data. The SNR of the signal prior to STFT calculation and feature extraction was varied by adding a certain amount of noise to obtain SNR between -10 and 10 dB in steps of 5 dB. As expected, a decreasing trend of accuracy with increasing SNR is reported for both types of features. The SVD based features appear to provide better classification results than the centroid based features, with average accuracy above 93% even with SNR equal to 0 dB. In Fig. 3 the classification accuracy as a function of SNR for different aspect angles is shown, for both centroid and SVD based features. The expected increase in accuracy with increasing SNR can be seen, as well as the higher accuracy at the most favourable aspect angles 2 and 1.

TABLE V
CLASSIFICATION ACCURACY FOR DIFFERENT CLASSIFIERS AND SNR – MULTISTATIC DATA COMBINED WITH THRESHOLD VOTING – CENTROID FEATURES – ASPECT ANGLE 2

Classifier Type	SNR [dB]				
	10	5	0	-5	-10
DLDA	91.1	90.8	85.7	91.9	77.2
DQDA	88.9	88.7	84.7	80.7	75.0
NB	85.1	83.3	80.5	76.4	69.5
NN3	84.9	84.5	82.4	79.9	74.4
NN5	94.1	84.6	81.2	78.4	74.0
CT	86.9	85.5	81.9	76.8	71.6
AVERAGE	88.5	86.2	82.7	80.7	73.6

TABLE VI
CLASSIFICATION ACCURACY FOR DIFFERENT CLASSIFIERS AND SNR – MULTISTATIC DATA COMBINED WITH THRESHOLD VOTING – SVD MATRIX FEATURES – ASPECT ANGLE 2

Classifier Type	SNR [dB]				
	10	5	0	-5	-10
DLDA	98.9	98.5	95.1	85.5	72.7
DQDA	96.4	95.9	93.4	83.0	75.8
NB	93.5	90.8	87.2	76.8	71.9
NN3	98.1	98.6	95.4	87.0	74.3
NN5	98.4	98.3	94.1	83.4	63.2
CT	98.4	98.4	94.9	85.5	78.2
AVERAGE	97.3	96.8	93.4	83.5	72.7

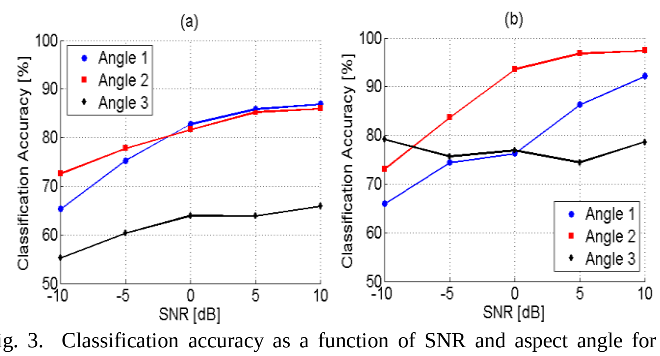

Fig. 3. Classification accuracy as a function of SNR and aspect angle for centroid based features (a) and for SVD-based feature (b)

C. *Computational efficiency*

The computational efficiency of the different combinations of classifiers and features was also investigated in terms of processing time and memory occupations. The classifiers were implemented in MATLAB and tested on the same desktop computer in the same conditions. The results are summarized in table 7, assuming calculations only for aspect angle 1. The nearest neighbor and the classification tree appear to be the fastest classifiers (approximately 4 s), followed by the discriminant analysis in linear (approximately 6.6 s) and quadratic form (approximately 8.6 s). It is interesting to notice the significant difference in processing time for the Naïve Bayes classifier using different features. This may be related to the fact that for the centroid case there are four features to be used jointly, whereas for the SVD case only one feature. The memory usage appears to be uniform with different classifiers, slightly higher for SVD features in comparison with centroid features.

TABLE VII
COMPUTATIONAL EFFICIENCY AND MEMORY USAGE FOR DIFFERENT CLASSIFIERS AND FEATURES

Classifier Type	Processing time [s]		Memory usage [MB]	
	SVD feat	Centroid feat	SVD feat	Centroid feat
DLDA	6.606	6.797	1115	1077
DQDA	8.696	8.686	1114	1083
NB	4.255	12.562	1117	1081
NN3	4.378	4.148	1120	1083
NN5	4.228	4.284	1119	1076
CT	4.037	4.239	1123	1076

IV. CONCLUSIONS

This letter discusses the use of human micro-Doppler signatures as collected by a multistatic radar system for personnel recognition. Three different sets of features were tested on experimental data, namely features based on individual SVD vectors, on the whole matrices deriving from SVD decomposition, and on the centroid of the micro-Doppler signatures, with the last two providing the best classification results. The impact of different parameters on the classification performance was investigated, namely three different aspect angles, six types of classifier, different values of SNR, and different approaches in combining multistatic data.

A single feature based on the whole matrix U derived from SVD appears to provide the best accuracy, above 98% for the most favorable aspect angle, but with degradation down to approximately 75 % for less favorable angles. The different types of classifier do not appear to have a very significant impact on the performance compared with other parameters such as aspect angles, SNR, and types of features.

Future work will investigate different deployment geometries of the multistatic radar nodes to optimize the classification performance and reduce this adverse effect of aspect angles. Additional data will also be collected from different subjects and for different activities to test the robustness of the proposed features.

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